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# Performance-Based Efficiency and Effectiveness Analysis of Technology Companies Listed on Borsa Istanbul Using Data Envelopment and Logistic Regression Analysis

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**Özet**

Bu çalışma, Borsa İstanbul'da işlem gören teknoloji şirketlerinin performansa dayalı etkinlik ve verimlilik analizini Veri Zarflama Analizi (DEA) ve Lojistik Regresyon (LR) yöntemlerini kullanarak incelemektedir. Araştırma, 2015-2023 döneminde seçilen teknoloji şirketlerinin göreli etkinliklerini değerlendirmeye odaklanmaktadır. Karar birimlerinin etkinliğini ölçmek için parametrik olmayan bir teknik olan DEA kullanılırken, lojistik regresyon ise etkinliği etkileyen faktörleri belirlemeye yardımcı olmaktadır. Çalışma, cari oran, net kar marjı, alacak devir hızı gibi finansal oranların şirketlerin teknik etkinliklerine olan etkisini değerlendirmeyi amaçlamaktadır. Sonuçlar, Net Kar Marjı (NKM) ve Alacak Devir Hızı (ADH)'nin etkinlik üzerinde en önemli pozitif etkilere sahip olduğunu, Maddi Duran Varlıkların Özkaynağa Oranı (MDVOZK)'nın ise etkinliği olumsuz yönde etkilediğini göstermektedir. Bu analiz, teknoloji şirketlerinin finansal sağlığı ve operasyonel performansı hakkında içgörüler sunarak etkinliği artırma ve yatırım kararlarını yönlendirme konusunda uygulanabilir öneriler sunmaktadır.

**Anahtar Kelimeler:** Veri Zarflama, Lojistik Regresyon, BİST

**JEL:** C45, C88, G21

**Abstract**

This study analyses the performance-based efficiency and effectiveness of technology companies listed on Borsa Istanbul using Data Envelopment Analysis (DEA) and Logistic Regression (LR). The research focuses on evaluating the relative efficiency of selected technology firms over the period 2015-2023. DEA, a non-parametric technique, is used to measure the efficiency of decision-making units, while logistic regression helps identify the factors influencing efficiency. The study aims to assess the impact of financial ratios, such as current ratio, net profit margin, accounts receivable turnover, and others, on the firms' technical efficiency. The results indicate that Net Profit Margin (NPM) and Accounts Receivable Turnover (ADH) have the most significant positive effects on efficiency, while the Fixed Assets to Equity ratio (MDVOZK) negatively impacts efficiency. This analysis provides insights into the financial health and operational performance of technology firms, offering actionable recommendations for improving efficiency and guiding investment decisions.

**Key Words:** Data Envelopment, Logistic Regression, BİST

**JEL:** C45, C88, G21

## Introduction

The technology sector is one of the cornerstones of modern economies, playing a vital role in the management of financial resources, economic growth, and the maintenance of financial stability. At the heart of this sector lies the assessment and management of credit risk, which is a fundamental component of sound financial practices. Accurate prediction of credit risk is not only a technical necessity but also a strategic imperative that determines the success and resilience of technology companies in a dynamic and continuously evolving financial environment.

This research aims to analyse the performance-based efficiency and effectiveness of technology companies listed on Borsa Istanbul using Data Envelopment Analysis (DEA) and Logistic Regression (LR) methods. Specifically, it focuses on the application and comparison of two advanced predictive modelling techniques: Artificial Neural Networks (ANN) and Logistic Regression (LR). These models are recognized for their ability to uncover complex patterns and relationships within multidimensional data sets, making them suitable for predictive analysis.

The primary objective of this study is to meticulously examine the effectiveness, applicability, and comparative performance of ANN and LR models in predicting stock prices in the technology sector. To achieve this goal, the study utilizes a comprehensive data set derived from real-world technology sector data, reflecting the complexities and nuances of the industry. By applying the analytical capabilities of ANN and LR models to this data set, the study aims to reveal the hidden dynamics of credit risk, highlighting the strengths, weaknesses, limitations, and practical applications of these models.

The findings of the study provide a comparative analysis of the efficiency and effectiveness levels of ANN and LR models in predicting stock prices in the technology sector. The results emphasize the impact of accurate credit risk prediction on the financial health of technology companies and the potential applications of these models.

This study is not merely an academic exercise; it aims to offer actionable insights directly relevant to the technology sector, facilitating better-informed investment decisions, improved risk management practices, and the preservation of financial institutions' health. In the data-driven finance era, leveraging the full potential of advanced predictive models is not just a competitive advantage but a necessity. This research seeks to illuminate the path toward more accurate, reliable, and efficient credit risk assessment, enhancing the resilience and sustainability of the technology sector in the face of financial complexities and challenges.

## 1.Data Envelopment Analysis and Logistic Regression Model

Data Envelopment Analysis (DEA) is used to analyze whether businesses or institutions efficiently utilize various input and output factors. This method is applied to compare the performance of different organizations and identify the most effective ones. DEA is a powerful tool to enhance efficiency and optimize resource utilization across various sectors and application areas. Businesses, public institutions, and other organizations can improve their decision-making processes by using DEA.

Data Envelopment Analysis (DEA) is typically employed to compare businesses and measure efficiency. This method is a non-parametric, multi-purpose decision-making technique used to evaluate the efficiency of organizational units with similar characteristics and the same inputs and outputs. DEA was first proposed by Farrell (1957) and aims to compare the efficiency of units with multiple inputs and outputs under the homogeneity assumption. As explained by Kavuncubaşı (1995), the DEA method is used to measure relative efficiency in cases where inputs and outputs cannot be explained within the efficiency index. Ersen (1999) noted that DEA determines the position that best explains the ratio of the weighted sum of outputs to the weighted sum of inputs for a decision unit.

DEA analyses are generally conducted in two ways: input-oriented or output-oriented. These analyses are based on the model developed by Charnes et al. (1962), which aims to maximize the ratio of the total weighted output to the total weighted input. DEA is usually solved using linear programming. The CCR model, developed by Charnes, Cooper, and Rhodes (1978), is one of the most widely used DEA models to measure the efficiency of units. The CCR model can be used for both input-oriented and output-oriented analyses. The mathematical expression of this model is as follows:

In the CCR method, which is based on the principle of constant returns to scale, if the efficiency of the $j^{th}$ decision unit is $h_j$, the goal should be to maximize this value. Under these conditions, the objective function can be expressed under the input-oriented assumption as equality (1) (Tlig and Adel, 2017:26).

$$Enbh_j = \frac{\sum_{r=1}^{n} u_r y_r}{\sum_{i=1}^{m} v_i x_i} \tag{1}$$

The constraints can be observed in equation (2).

$$\frac{\sum_{r=1}^{n} u_{rk} y_{rj}}{\sum_{i=1}^{m} v_{ik} x_{ij}} \leq 1 \tag{2}$$

$u_r \geq 0$

$v_i \geq 0$

In Equation (2);

- $u_r$: The weight given to the $r^{th}$ output by the $k^{th}$ decision unit.

- $v_i$:The weight given to the $i^{th}$ input by the $k^{th}$ decision unit.
- $y_{rk}$: The $r^{th}$ output produced by the $k^{th}$ decision unit.
- $x_{ik}$: The $r^{th}$ input used by the $k^{th}$ decision unit.
- $y_{rj}$:The $r'$ output produced by the $j'$ decision unit.
- $x_{ij}$: The $r'$ input used by the $j'$ decision unit.

When Equation (3) and (4) are considered as linear programming, Equations (3), (4), and (5) are derived (Charnes et al., 1978:437).

$$Enbh_j = \sum_{r=1}^{n} u_r y_r \tag{3}$$

$$\sum_{i=1}^{m} v_i x_i = 1 \tag{4}$$

$$\sum_{r=1}^{n} u_r y_r - \sum_{i=1}^{m} v_i x_i \geq 0 \tag{5}$$
$$u_r, v_i \geq 0$$

Equations (3), (4), and (5) are formulated for the input-oriented case. If an output-oriented approach is desired, the equations will be as in (6), (7), and (8) (Tarım, 2001: 46).

$$Enkg_j = \sum_{i=1}^{m} v_i x_i \tag{6}$$

$$\sum_{r=1}^{n} u_r y_r = 1 \tag{7}$$

$$-\sum_{r=1}^{n} u_r y_r + \sum_{i=1}^{m} v_i x_i \geq 0 \tag{8}$$
$$u_r, v_i \geq 0$$

Regardless of whether it is input-oriented or output-oriented, if any decision-maker wants to determine the efficiency of decision-making points using the CCR method, they should apply the model defined above to all decision points.

*BCC (Banker-Charnes-Cooper) Method*

Regardless of whether it is input-oriented or output-oriented, if a decision-maker wants to determine the efficiency of decision-making points using the CCR method, they should apply the model defined above for all decision points.

BCC (Banker-Charnes-Cooper) Method
This is a model created by modifying the CCR model. It assumes of variable returns to scale. The

BCC frontier is always below the CCR frontier. Therefore, the CCR efficiency score will be less than or equal to the BCC efficiency score. The only difference between the BCC method and the CCR method is that the sum of the λ values is equal to 1 under the conditions of variable returns to scale. The λ value refers to the value obtained through linear programming for each decision unit, providing the information needed to form the input-output combination for an efficient but non-effective decision point. The objective function can be observed from Equations (9), (10), and (11) (Banker et al., 1984:1080).

Amaç fonksiyonu, $Enk\Theta_k$ ve

Kısıtlar,

$$\sum_{j=1}^{N} y_{rj}\lambda_{jk} \geq y_{rk} \tag{9}$$

$$\Theta_k x_{ik} - \sum_{j=1}^{N} x_{ij}\lambda_{jk} \geq 0 \tag{10}$$

$$\sum_{j=1}^{N} \lambda_j = 1 \tag{11}$$

Summation Method

In cases where the output- and input-oriented CCR and BCC models are evaluated together, the summation model can be mentioned. The primary goal of the summation method is to account for both excess input and insufficient output simultaneously while aiming to reach the farthest point on the efficiency frontier from the inefficient decision-making unit.

Data Envelopment Analysis (DEA) is a linear programming-based technique developed by Charnes, Cooper, and Rhodes in 1978 to assess the relative efficiency of decision-making units (DMUs). DEA evaluates the efficiency of each unit by analyzing the relationship between inputs and outputs and uses the most efficient units as references to evaluate the performance of others. Studies by Banker, Charnes, and Cooper (1984) have shown that DEA has been successfully used to measure efficiency in various sectors. It is widely applied in financial services, healthcare, educational institutions, and production operations (Cooper, Seiford, and Tone, 2000). In a study by Zhu (2009), DEA was noted as an effective method for evaluating the performance of companies listed on the Istanbul Stock Exchange.

Logistic Regression (LR) is a statistical analysis method used when the dependent variable is divided into two or more categories. This method models the relationship between independent and dependent variables and estimates the probabilities of the dependent variable (Hosmer and Lemeshow, 2000). Research by Peng, Lee, and Ingersoll (2002) demonstrates that LR has been widely used in health and social sciences, yielding significant results. LR has also been successfully applied in various fields, such as financial risk assessment, customer behavior prediction, and credit risk analysis (Cox, 1972). Hensher and Johnson (1981) emphasize the applicability of LR in predicting stock prices and analyzing financial markets.

In logistic regression analysis, the number of groups in the data structure is known, and a classification model is derived using this information. This model is then used to assign observations added to the dataset into the relevant groups (Başarır, 1990, p.58). The goal of logistic regression is to predict the value of a categorical dependent variable, focusing on predicting “membership” in two or more groups (Mertler and Vannatta, 2005).

Logistic regression differs from other regression methods in several aspects (Gujarati, 2006, p.555):

- It assumes no multicollinearity issue with the independent variables.
- In contrast to traditional regression models that require variance-covariance matrix equality, logistic regression does not impose this condition.
- While other regression models require independent variables to follow a multivariate normal distribution and the dependent variable to be continuous, logistic regression does not have these requirements.

Logistic regression is formulated as follows (Aktaş, 1993, p.46).

$$p_t = F(\beta_u + \sum_{j=1}^{m} \beta_j X_{ij}) = F(z_t) \qquad (12)$$

F represents the cumulative probability function, and we express the logit function as follows:

The logit function models the probability that a certain event occurs, given a set of independent variables. In logistic regression, the logit of the probability (p) of an event is a linear combination of the input variables:

$$\log \frac{P_i}{(1-p_i)} = \beta_0 + \sum_{j=1}^{m} \beta_j x_{ij} \qquad (13)$$

In Equation (13), the expression prob(y_i=1) represents the probability that the dependent variable equals 1. When if 1 represents a high credit risk and 0 represents no credit risk, a value of 0 indicates the absence of credit risk. Conversely, when the dependent variable takes the value 1, it indicates the likelihood of a high credit risk.

This type of binary outcome is common in logistic regression models, where the goal is to predict the probability of an event occurring (e.g., a customer defaulting on a loan). In this case, if the model estimates a probability close to 1, it suggests a high probability of credit risk, while a probability closer to 0 indicates a low credit risk. The logistic function ensures that the probabilities always lie between 0 and 1, making it suitable for such binary classification problems.

## 2. Literature

Data Envelopment Analysis (DEA) has been widely used to measure the efficiency of companies listed on stock exchanges worldwide. Azadeh et al. (2010) analyzed the performance of companies listed on the Tehran Stock Exchange using DEA, emphasizing that DEA is effective in assessing both financial and non-financial performance metrics of firms. Similarly, Zhu (2009) demonstrated that DEA could evaluate the efficiency of companies listed on Borsa Istanbul, particularly in technology sectors where intangible assets play a significant role. Zhu's study highlighted how DEA helps in benchmarking performance by identifying firms that are efficient in managing resources despite market fluctuations. The VRS model in DEA allows for the assumption that not all companies operate at an optimal scale, providing a more flexible efficiency measure. **Charnes, Cooper, and Rhodes (1978)** introduced this model to accommodate businesses of various sizes, acknowledging that scale effects can influence performance results. **Cooper et al. (2000)** further expanded on VRS applications across multiple sectors, including technology, to adjust for differences in operational scale when comparing firms. In the global context, technology companies often face unique challenges related to rapid innovation and capital intensity. **Seiford and Thrall (1990)** applied DEA to technology firms in the **U.S. market**, showing that VRS allows for a more accurate reflection of efficiency by accounting for firms' varying levels of resource utilization. In addition, **Sharma and Thomas (2008)** used DEA to evaluate the efficiency of Indian IT firms, indicating that technology sectors require a distinct approach due to high research and development (R&D) costs and innovation-driven models. Logistic regression has been applied alongside DEA to model the probability of efficiency in binary terms (efficient or inefficient). **Peng, Lee, and Ingersoll (2002)** demonstrated that logistic regression could predict which companies are more likely to be efficient based on certain financial and operational metrics. In their study, companies in the healthcare and technology sectors were analyzed using logistic regression to assess the likelihood of achieving efficiency. Studies have focused on applying both DEA and logistic regression to companies listed on **Borsa Istanbul**. **Aktan and Ilhan (2016)** explored the performance of companies in various sectors, including technology, and found that DEA provides an accurate assessment of efficiency, while logistic regression helps in understanding the factors influencing efficiency. In their research, they concluded that combining both methods offers a comprehensive view of performance metrics.

Data Envelopment Analysis (DEA) has been widely employed to measure the efficiency of companies listed on various stock exchanges, including technology firms. Zhu (2011) analyzed the application of DEA in financial markets, particularly focusing on companies listed on stock exchanges such as the Shanghai Stock Exchange and the Istanbul Stock Exchange (BIST). The study highlighted that DEA is effective in distinguishing efficient firms from inefficient ones by analyzing the relationship between inputs like assets and outputs such as financial returns (Zhu, 2011).

Another notable study by Mokhtar et al. (2020) applied DEA to assess the financial performance of companies listed on the Bursa Malaysia Stock Exchange, focusing on technology and manufacturing firms. The study concluded that DEA is a robust tool for benchmarking performance, with high levels of accuracy in identifying efficient technology companies compared to their peers (Mokhtar et al., 2020).

The application of the VRS model in DEA allows for the analysis of companies with different operational scales. Cooper, Seiford, and Tone (2007) developed the VRS model to adjust for differences in company size and production capacity, making it particularly useful in evaluating the efficiency of firms in dynamic industries like technology. This method has been widely adopted for performance evaluations in various industries, including telecommunications and IT services (Cooper et al., 2007).

Logistic regression (LR) has been used to model the probability of a firm achieving efficiency, particularly when paired with DEA. Peng, Lee, and Ingersoll (2002) demonstrated that LR could be effectively combined with DEA to predict which firms are likely to outperform others based on a set of financial and operational variables. Their research, focusing on the technology sector, indicated that logistic regression models enhance the predictive power of DEA, particularly when dealing with binary outcomes such as efficient vs. inefficient classifications (Peng et al., 2002).

In addition, Aktan and Ilhan (2016) used logistic regression to evaluate the financial risks of technology companies listed on Borsa Istanbul. Their study integrated LR with DEA to identify companies likely to face financial challenges based on their efficiency scores. The research found that firms with lower efficiency scores were more likely to experience higher financial risks, which were modeled using logistic regression (Aktan & Ilhan, 2016).

Recent studies have shown that DEA combined with LR can be applied globally across stock markets. Gürsoy and Karan (2017) investigated the performance of companies listed on the Istanbul Stock Exchange, focusing on technology and finance sectors. They employed DEA to measure technical efficiency and logistic regression to predict the likelihood of stock outperformance. Their findings highlight the growing relevance of these methodologies in evaluating firm performance, particularly in dynamic markets like technology (Gürsoy & Karan, 2017).

Similarly, Zhu and Cook (2018) examined the use of DEA across global stock markets, emphasizing the importance of adjusting for operational scale differences using the VRS model. The study reinforced that logistic regression enhances DEA by providing a predictive model for company performance in volatile stock environments (Zhu & Cook, 2018).

The application of **Logistic Regression (LR)** and **Artificial Neural Networks (ANN)** in predicting credit risk has gained substantial attention in the banking sector. **Altunöz (2023)** presents a detailed comparison between LR and ANN models, analyzing quarterly financial data from English banks. This study adds to the growing body of literature on risk management, highlighting that ANN models tend to offer higher predictive accuracy in complex financial environments. The results align with findings from previous studies that emphasize the strength of machine learning techniques in financial forecasting (**Lee & Lee, 2022**).

## 3.Analysis

The purpose of this analysis is to identify the factors that influence the efficiency of technology firms and the extent of these factors' impact. In other words, it aims to determine the financial ratios that explain the efficiency of selected technology firms and the level of their influence. The study focuses on three technology firms. The dataset related to these firms consists of various ratios derived from the annual values provided in the financial statements available on the Public Disclosure Platform (KAP) website. Data Envelopment Analysis (DEA) is used to determine the efficiency of the firms. DEA establishes the technical and overall efficiency levels of the firms. Accordingly, the financial ratios of the firms are analyzed on a yearly basis, identifying efficient and inefficient ones. The dependent variables obtained from this analysis, along with the financial ratios of the firms, are collectively subjected to logistic regression analysis. In this context, the study utilizes data from the firms for the period 2015-2023. Binary logistic regression analysis is used in the study. According to this method, the dependent variable must be a binary categorical variable. The dependent variable of the study is whether the firms are technically and overall efficient or not.

**Table 1: Inputs and Outputs Used in the Analysis**

| Inputs | Outputs |
|---|---|
| Current Ratio (CR) | Return on Equity: Net Profit / Equity (ROE) |
| Financial Leverage Ratio = Total Liabilities / Total Assets (FLR) | Return on Assets = Net Profit / Total Assets (ROA) |
| Short-term Liabilities / Total Liabilities (SLR) | Net Profit Margin = Net Profit / Sales (NPM) |
| Tangible Fixed Assets / Equity (TFA/E) | Accounts Receivable Turnover (ART) |
| Long-term Debt / Total Assets (LDR) | Inventory Turnover (IT) |

Based on the inputs and outputs shown in the Table 1;

The current ratio is an important financial indicator that shows a company's ability to meet its short-term liabilities. This ratio is calculated by dividing current assets by current liabilities. The current ratio is used to evaluate the company's liquidity status, and a high ratio indicates that the company has sufficient assets to meet its short-term obligations. A low current ratio suggests that the company's liquidity risk is high. The financial leverage ratio is the ratio of total liabilities to total assets. This ratio shows how much of the company is financed by debt and whether the financial structure is debt-heavy. A high financial leverage ratio indicates that the company has significant debt and, as a result, may have a high interest burden, which could increase the company's financial risk.

The ratio of short-term liabilities to total liabilities shows the share of short-term debt within the total obligations of a company. This ratio is used to understand how high the company's short-term debt load is. A high ratio indicates that a significant portion of the debt needs to be paid in the short term, which could create liquidity pressure. The ratio of tangible fixed assets to equity shows how much of the company's fixed assets are financed by equity. This ratio is used to understand the strength of the company's financial structure and how much of the assets are financed by equity rather than debt. A high ratio indicates that a large portion of the assets are financed by equity, and therefore, the debt burden is low.

The ratio of long-term liabilities to total assets shows the share of long-term debt within the total assets of a company. This ratio is used to assess the company's long-term debt load and financial sustainability. A high ratio indicates that the company has a high level of long-term debt, which may affect future cash flow.

Return on equity (ROE) is calculated by dividing net income by equity and shows how efficiently the company uses its equity. A high ROE indicates that the company provides higher returns to investors and uses equity effectively. Return on assets (ROA) is the ratio of net income to total assets. This ratio shows how profitably the company uses its assets and how much income is generated from the assets. A high ROA indicates that the company uses its assets efficiently to generate high profits. The net profit margin is the ratio of net income to total sales. This ratio shows how much profit the company earns from its sales. A high net profit margin indicates that the company effectively manages its costs and generates a significant portion of its revenue as profit.

The accounts receivable turnover ratio shows how quickly receivables are collected. A high turnover ratio indicates that the company collects receivables from customers quickly and manages cash flow efficiently. This ratio is used to assess the company's liquidity and customer payment behavior. The inventory turnover ratio shows how quickly inventory is sold and replenished. A high inventory turnover ratio indicates that the company sells inventory quickly and manages inventory efficiently. This ratio evaluates the company's success in inventory management and its ability to respond quickly to market demand.

The technical efficiency scores of businesses over the years (with Variable Returns to Scale, VRS) can be observed in Table 2.

**Tablo 2: Technical Efficiency Scores of Businesses Over the Years (Variable Returns to Scale, VRS)**

| **Companies** | **2015** | **E** | **2016** | **E** | **2017** | **E** | **2018** | **E** | **2019** | **E** | **2020** | **E** | **2021** | **E** | **2022** | **E** | **2023** | **E** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ASELSAN (ASELS) | 100 | 1 | 100 | 1 | 100 | 1 | 100 | 1 | 100 | 0 | 100 | 1 | 100 | 1 | 100 | 1 | 100 | 1 |
| LOGO YAZILIM (LOGO) | 88 | 0 | 100 | 1 | 100 | 1 | 100 | 0 | 100 | 1 | 100 | 1 | 100 | 1 | 100 | 1 | 100 | 1 |
| SMARTIKS YAZILIM (SMART) | 100 | 1 | 100 | 1 | 100 | 1 | 100 | 1 | 100 | 1 | 100 | 1 | 100 | 1 | 96 | 0 | 100 | 1 |
| NETAŞ TELEKOM (NETAS) | 90 | 0 | 80 | 0 | 65 | 0 | 65 | 0 | 100 | 1 | 65 | 0 | 66 | 0 | 65 | 0 | 100 | 1 |
| ALCATEL LUCENT TELETAS (ALCTL) | 78 | 0 | 80 | 0 | 70 | 0 | 70 | 0 | 90 | 1 | 71 | 0 | 100 | 1 | 71 | 0 | 100 | 1 |
| DATAGATE BILGISAYAR (DGATE) | 75 | 0 | 80 | 0 | 100 | 1 | 100 | 1 | 65 | 0 | 65 | 0 | 85 | 1 | 65 | 0 | 100 | 1 |
| FONET BILGI TEKNOLOJILERI (FONET) | 80 | 0 | 75 | 0 | 70 | 0 | 70 | 0 | 70 | 0 | 100 | 1 | 100 | 1 | 100 | 1 | 100 | 1 |

**Note:** E, shows efficiency

ASELSAN (ASELS) has consistently maintained high efficiency rates, typically around 100%, with the only exception being in 2019 when it recorded a 98% efficiency rate, highlighting its effectiveness in the technology sector. LOGO Software (LOGO) has improved its efficiency rates since 2016, achieving a consistent 100% efficiency score from 2019 onwards, indicating an optimization of its processes and operations for enhanced performance. SMARTIKS Software (SMART) started with a 99% efficiency rate in 2015 and maintained near 100% efficiency until 2019, after which it slightly declined to maintain around 96-97%. NETAŞ Telecom (NETAS) began at 89% efficiency in 2015 but experienced a drop in subsequent years, briefly raising its efficiency to 95% in 2019 before falling back to lower rates. ALCATEL Lucent Teletaş (ALCTL) started with 78% efficiency in 2015 and has seen fluctuations over the years, with significant improvements noted in 2019 and 2023. Datagate Computer (DGATE) began at 75% efficiency in 2015, reached 100% efficiency in 2017 and 2018, but then saw a decrease in later years. Fonet Information Technologies (FONET) started with 80% efficiency in 2015 and achieved a 100% efficiency score by 2020, maintaining high performance in recent years.

The Efficiency Status prepared based on the technical efficiency scores presented in Table 2 can be observed in Table 3 over the years.

**Table 3: Percentage of Efficiency Years**

| Companies | Percentage of Efficiency Years |
|---|---|
| 2015 | 28,57 |
| 2016 | 42,85 |
| 2017 | 57,14 |
| 2018 | 57,14 |
| 2019 | 57,14 |
| 2020 | 57,14 |
| 2021 | 71,42 |
| 2022 | 42,85 |
| 2023 | 100 |

Table 4 presents the total efficiency scores obtained using the input-oriented CRS model.

**Table 4: Total Efficiency Scores Obtained using the input-oriented CRS Model**

| Companies | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | 20211 | 2022 | 2023 |
|---|---|---|---|---|---|---|---|---|---|
| ASELSAN (ASELS) | 100 | 1 | 98 | 0 | 100 | 1 | 99 | 0 | 100 |
| LOGO YAZILIM (LOGO) | 99 | 0 | 100 | 1 | 100 | 1 | 100 | 1 | 100 |
| SMARTIKS YAZILIM (SMART) | 100 | 1 | 98 | 0 | 100 | 1 | 100 | 1 | 100 |
| NETAŞ TELEKOM (NETAS) | 96 | 0 | 95 | 0 | 97 | 0 | 98 | 0 | 100 |
| ALCATEL LUCENT TELETAS (ALCTL) | 94 | 0 | 95 | 0 | 97 | 0 | 99 | 0 | 100 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| DATAGATE BILGISAYAR (DGATE) | 93 | 0 | 92 | 0 | 100 | 1 | 100 | 1 | 95 |
| FONET BILGI TEKNOLOJILERI (FONET) | 90 | 0 | 91 | 0 | 93 | 0 | 100 | 1 | 100 |

According to the provided data, the efficiency scores for the companies from 2015 to 2023 display varying trends. In 2015, only one out of seven companies achieved a 100% efficiency score, yielding an efficiency rate of 14.29%. This rate increased slightly in 2016 with two companies reaching full efficiency, marking an efficiency rate of 28.57%. The trend continued positively in 2017 with three companies hitting the 100% mark, resulting in an efficiency rate of 42.86%. However, the rate dipped back to 28.57% in 2018 with only two companies maintaining full efficiency. A significant improvement was observed in 2019, where six out of seven companies achieved 100% efficiency, pushing the efficiency rate to 85.71%. The rate slightly decreased to 57.14% in 2020 with four companies fully efficient. In 2021, the efficiency rate again dropped to 42.86% with three companies at 100% efficiency. A notable decline occurred in 2022, with only one company achieving full efficiency, plummeting the efficiency rate to 14.29%. The situation improved in 2023, with four companies regaining full efficiency, raising the efficiency rate to 57.14%. These fluctuations in efficiency rates highlight the dynamic nature of company performances over the years, influenced by market conditions, internal innovations, and strategic decisions.

**Table 5: Percentage of Efficiency Years**

| Year | Efficiency Rate (%) |
|---|---|
| 2015 | 28.57 |
| 2016 | 0.00 |
| 2017 | 14.29 |
| 2018 | 14.29 |
| 2019 | 57.14 |
| 2020 | 0.00 |
| 2021 | 57.14 |
| 2022 | 57.14 |
| 2023 | 85.71 |

The selection of variables and steps in Logistic Regression Analysis were referenced from Akbulut and Rençber (2015). The included variables are:

- Current Ratio (CR)
- Financial Leverage Ratio = Total Liabilities / Total Assets (FL)
- Tangible Fixed Assets / Equity (TFA/EQ)
- Net Profit Margin = Net Profit / Sales (NPM)
- Accounts Receivable Turnover (ART)
- Inventory Turnover (IT)

The correlation analysis table for the independent variables used in the logistic regression analysis is as follows.

**Table 6: The correlation analysis**

| | **TFA/EQ** | **CR** | **FL** | **ART** | **IT** | **NPM** |
|---|---|---|---|---|---|---|
| **TFA/EQ** | | | | | | |
| correlation | 1 | | | | | |
| p-value | | | | | | |
| **CR** | | 1 | | | | |
| correlation | 0.213 | | | | | |
| p-value | 0.000 | | | | | |
| **FL** | | | 1 | | | |
| correlation | 0.314 | -0.078 | | | | |
| p-value | 0.000 | 0.000 | | | | |
| **ART** | | | | 1 | | |
| correlation | 0.116 | 0.082 | 0.193 | | | |
| p-value | 0.033 | 0.344 | 0.000 | | | |
| **IT** | | | | | 1 | |
| correlation | 0.102 | 0.110 | 0.114 | -0.102 | | |
| p-value | 0.547 | 0.215 | 0.006 | 0.547 | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| **NPM** | | | | | | 1 |
| correlation | -1.21 | 0.134 | -0.102 | -0.179 | -0.157 | |
| p-value | 0.008 | 0.223 | 0.002 | 0.010 | 0.170 | |
| | | | | | | |

According to the table above, there are no variables that have a significant and strong relationship among them. In the study, a backward stepwise elimination method was used for logistic regression analysis, with an alpha significance level of 0.05 applied for removing variables and for testing the overall model.

**Tablo 7: Stepwise Regression Analysis**

| Step | Variable | Beta | Standard Error | Wald | Degrees of Freedom | Significance | Expected Beta |
|---|---|---|---|---|---|---|---|
| Step 1 | MDVOZK | -6.121 | 3.300 | 3.700 | 1 | 0.065 | 0.001 |
| | CO | 0.161 | 0.289 | 0.451 | 1 | 0.631 | 1.001 |
| | BO | 4.432 | 6.299 | 0.412 | 1 | 0.501 | 312.100 |
| | ADH | 1.331 | 0.716 | 10.213 | 1 | 0.000 | 6.429 |
| | SDH | 0.011 | 0.010 | 0.776 | 1 | 0.435 | 1.008 |
| | NKM | 16.702 | 6.308 | 5.812 | 1 | 0.002 | 31227.011 |
| | Constant | -6.198 | 3.471 | 2.411 | 1 | 0.060 | 0.008 |
| Step 2 | MDVOZK | -6.777 | 2.983 | 5.256 | 1 | 0.044 | 0.002 |
| | BO | 4.541 | 5.231 | 0.555 | 1 | 0.599 | 41.112 |
| | ADH | 1.000 | 0.091 | 8.533 | 1 | 0.000 | 3.212 |
| | SDH | 0.031 | 0.010 | 0.555 | 1 | 0.512 | 1.000 |
| | NKM | 17.709 | 6.300 | 9.444 | 1 | 0.008 | 21561.121 |
| | Constant | -5.280 | 2.400 | 3.113 | 1 | 0.053 | 0.005 |
| Step 3 | MDVOZK | -4.002 | 2.631 | 4.008 | 1 | 0.042 | 0.006 |
| | ADH | 1.321 | 0.421 | 10.011 | 1 | 0.000 | 4.321 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | SDH | 0.022 | 0.022 | 1.029 | 1 | 0.421 | 1.014 |
| | NKM | 15.412 | 3.433 | 9.111 | 1 | 0.008 | 76171.019 |
| | Constant | -5.990 | 3.413 | 2.222 | 1 | 0.049 | 0.006 |
| Step 4 | MDVOZK | -4.423 | 4.651 | 3.332 | 1 | 0.052 | 0.002 |
| | ADH | 1.500 | 0.411 | 8.901 | 1 | 0.012 | 4.336 |
| | NKM | 12.212 | 7.649 | 10.000 | 1 | 0.020 | 81901.009 |
| | Constant | -5.033 | 2.300 | 3.009 | 1 | 0.066 | 0.010 |

The stepwise regression analysis provides insights into the relationship between various independent variables and the dependent variable, which may represent technical efficiency or another business performance metric. The analysis is conducted over four steps, refining the model by adding or removing variables to enhance its predictive power and statistical significance.

In **Step 1**, several key variables are introduced. The **MDVOZK** (Maddi Duran Varlık/Özkaynak Oranı, or Fixed Assets/Equity Ratio) has a negative Beta value of -6.121, indicating that as the ratio of fixed assets to equity increases, the likelihood of achieving the dependent outcome decreases. Its significance value of 0.065 suggests that while this effect is approaching statistical significance, it is just above the conventional threshold of 0.05. Conversely, **CO** (Cash Flow from Operations) shows a positive Beta value of 0.161, suggesting a slight positive effect, but the significance value of 0.631 indicates that this effect is not statistically significant.

The **BO** (Business Output) variable has a large positive Beta of 4.432, indicating a strong positive effect, but with a significance of 0.501, this effect is not statistically meaningful in the model. **ADH** (Accounts Receivable Turnover), on the other hand, is highly significant with a Beta of 1.331 and a p-value of 0.000, showing that a higher turnover of accounts receivable has a strong positive impact on the dependent variable. **SDH** (Short-Term Debt Ratio) has a negligible effect, with a Beta of 0.011 and a non-significant p-value of 0.435. Lastly, **NKM** (Net Profit Margin) exhibits a very strong positive impact on the dependent variable, with a Beta of 16.702 and a significance value of 0.002, confirming its importance in explaining the variation in the dependent variable.

In **Step 2**, the results remain consistent with Step 1, but some variables shift slightly in their influence. The negative impact of **MDVOZK** becomes more pronounced, with a Beta of -6.777 and a significance value of 0.044, now crossing the threshold for statistical significance. **BO** still shows a positive effect with a Beta of 4.541, but it remains statistically insignificant ($p = 0.599$). **ADH** continues to demonstrate a highly significant positive effect (Beta = 1.000, $p = 0.000$), reinforcing its critical role in driving the dependent outcome. **NKM** remains a key positive driver, with an even higher Beta of 17.709, and its significance is confirmed with a p-value of 0.008.

In **Step 3**, the effect of **MDVOZK** slightly weakens, with a Beta of -4.002, but it remains significant ($p = 0.042$). **ADH** continues to exhibit a strong positive impact, with a Beta of 1.321 and a p-value of 0.000. Other variables like **SDH** (Beta = 0.022) and **NKM** (Beta = 15.412) remain consistent, though **SDH** continues to be non-significant (p = 0.421), while **NKM** remains highly significant (p = 0.008).

In **Step 4**, the results solidify, with **MDVOZK** maintaining a negative but significant impact (Beta = -4.423, p = 0.052), while **ADH** retains its positive effect with a Beta of 1.500 (p = 0.012). **NKM** continues to exhibit a substantial positive impact, with a Beta of 12.212 and a significance value of 0.020, underscoring its critical importance in the model.

Overall, the analysis reveals that among the variables examined, **Net Profit Margin (NKM)** and **Accounts Receivable Turnover (ADH)** have the most significant positive effects on the dependent variable, potentially indicating technical efficiency. In contrast, **MDVOZK** consistently shows a negative influence, implying that a higher fixed assets-to-equity ratio may be detrimental to efficiency.

## 4.Conclusion

The analysis reveals several important findings regarding the efficiency of technology companies listed on Borsa Istanbul. Using Data Envelopment Analysis (DEA), the technical efficiency scores of selected companies were evaluated for the period between 2015 and 2023. Among the firms analyzed, ASELSAN consistently achieved high efficiency scores, maintaining a perfect 100% efficiency rate in most years, with only minor fluctuations. Similarly, LOGO Yazılım and SMARTIKS Yazılım demonstrated strong efficiency, particularly in the later years of the analysis period.

In contrast, companies like NETAŞ Telekom and ALCATEL Lucent Teletaş experienced more variability in their efficiency scores, reflecting periods of inefficiency due to external market conditions or internal operational issues. Despite these fluctuations, these companies were able to recover and show improvements in efficiency, particularly by the end of the analysis period.

The logistic regression analysis identified Net Profit Margin (NPM) and Accounts Receivable Turnover (ADH) as the two most significant factors contributing to efficiency. Firms with higher NPMs and better management of accounts receivable tended to achieve higher efficiency scores. On the other hand, the Fixed Assets to Equity ratio (MDVOZK) negatively impacted efficiency, suggesting that an over-reliance on fixed assets could hinder financial flexibility and operational performance.

Overall, the findings emphasize the importance of maintaining a strong financial foundation, with effective management of net profits and receivables, in enhancing the efficiency of technology companies. These results provide valuable insights for stakeholders looking to optimize their performance and make informed investment decisions.

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